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Probability and conspiratorial thinking

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Abstract

Conspiracy theories as alternative explanations for events and states of affairs enjoy widespread popularity. We test one possible explanation for why people are prone to conspiratorial thinking: We hypothesize that conspiratorial thinking as an explanation for events increases as the probability of those events decreases. In order to test this hypothesis, we have conducted five experiments in which participants were exposed to different information about probabilities of fictional events. The results of all experiments support the hypothesis: The lower the probability of an event, the stronger participants embrace conspiratorial explanations. Conspiratorial thinking, we conclude, potentially represents a cognitive heuristic: A coping mechanism for uncertainty.

1 Introduction: Conspiratorial beliefs and errors in probabilistic thinking

A conspiracy theory is a particular kind of alternative explanation for some event or some state of affairs in the world. Conspiracy theories posit that the "common explanation" for an event or state of affairs is false, and that, in

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reality, individuals or organizations have caused the event or state of affairs for nefarious reasons (Clarke, 2002; Keeley, 1999). From a purely epistemological point of view, conspiracy theories represent beliefs that are not justified very well, or not at all. This means that the epistemic shortcoming of conspiratorial beliefs is not contingent on their truth status: Even though the propositional content of conspiracy theories can be accidentally true, the way the belief in conspiracy theories is justified is defective. In that sense, conspiracy theories' "crippled" (Sunstein & Vermeule, 2009) epistemology represents a case of the Gettier problem (Gettier, 1963), or, more generally, a case of epistemic luck (Pritchard, 2004).

Given the epistemic shortcoming of conspiracy theories, the prevalence of conspiratorial thinking is somewhat surprising: Rather than being a fringe occurrence, belief in conspiracy theories is fairly common (Oliver & Wood, 2014a, 2014b), and, furthermore, belief in conspiracy theories can affect real-world behavior and decision-making (Jolley & Douglas, 2014b, 2014a; K. Douglas, Sutton, Jolley, & Wood, 2015). The fact that conspiracy theories are an everyday phenomenon means that accounts of conspiratorial thinking as pathologies (Barron, Morgan, Towell, Altemeyer, & Swami, 2014; Bentall, Kinderman, & Kaney, 1994; Darwin, Neave, & Holmes, 2011) or consequences of maladaptive traits (Swami, Weis, Lay, Barron, & Furnham, 2016) probably offer only a partial explanation. While it is possible that a subset of conspiratorial reasoning is caused by pathologies of the mind and anomalous personality traits, it is highly improbable that every conspiratorial belief can be explained in this manner. A different and complementary perspective on conspiratorial reasoning is not one of anomaly, but of normalcy: Conspiratorial reasoning as a consequence of general and universal cognitive limitations (Boudry & Braeckman, 2012). From this point of view, cognitive patterns in the context of conspiracy theories, such as the need for cognitive closure and explanatory completeness (Marchlewska, Cichocka, & Kossowska, 2017; Leman & Cinnirella, 2013; Basham, 2001), the need for making sense of high-impact events (Leman & Cinnirella, 2007; van Prooijen & van Dijk, 2014), and the need for clear agency (K. M. Douglas, Sutton, Callan, Dawtry, & Harvey, 2016), are not pathologies, but rather forms of cognitive heuristics, or cognitive biases.

1.1 Hypotheses

Cognitive biases are systematic errors in human cognition that often arise in situations in which we need to subjectively assess probabilities, either explicitly or implicitly (Tversky & Kahneman, 1974). It has been suggested that conspiratorial thinking is a coping mechanism for uncertainty (Franks, Bangerter, & Bauer, 2013), but, even though there is some evidence that conspiratorial thinking is linked to errors in probabilistic thinking (Brotherton & French, 2014; Dagnall, Denovan, Drinkwater, Parker, & Clough, 2017), the specific hypothesis of conspiratorial thinking as a heuristic for coping with uncertainty has not yet been put to the empirical test. We fill this gap with five experiments that test the following hypothesis: *The lower the probability of an event, the stronger the belief in a conspiratorial explanation of the event, and the weaker the belief in the common explanation of the event.*

In addition to our main hypothesis, we include two potential mediating factors in our experiments. As mentioned in the previous section, there is some evidence that conspiratorial reasoning might be more prominent when the events in question are of higher impact for society (Leman & Cinnirella, 2007; van Prooijen & van Dijk, 2014). We include this mediating factor in our study and hypothesize that *belief in a conspiratorial explanation is stronger in a high-impact scenario than in a low-impact scenario.* We define a low-impact event as an event that does not affect society as a whole, but only a very small group of people.

A second potentially mediating factor is the clarity of a motive for conspirators to conspire. A prominent feature of conspiracy theories and conspiratorial arguments is intentionality, or the presence of an ulterior, yet clear motive (Uscinski & Parent, 2014, 43). We include the presence of a clear ulterior motive as a potential mediating factor in our study and hypothesize that *belief in a conspiratorial explanation is stronger in a scenario with a clear ulterior motive.*

2 Design, data, methods

2.1 Five experiments

We test one main and two auxiliary hypotheses, as described in the previous section. In order to do so adequately, we conducted five separate experiments. The first of those experiments was designed to simply test the impact of event probabilities. Experiments two and three test the impact of event probabilities, and in addition, they are low-impact events either without a clear ulterior motive (experiment two) or with a clear ulterior motive (experiment three). Experiments four and five test the impact of event probabilities, and in addition, they are high-impact events either without a clear ulterior motive (experiment four) or with a clear ulterior motive (experiment five)

2.2 Recruitment of participants

Participants for the experiments presented in this paper were recruited on the crowdsourcing platform Clickworker (Lutz, 2015). Each participant was remunerated with €0.15 for completing a short survey that was the experiment. All five experiments were designed to take around one minute to complete. The experiments were conducted with version 2.63.1 of the open-source survey software LimeSurvey (LimeSurvey Project Team / Carsten Schmitz, 2012).

For experiment one (two experimental groups), we commissioned 250 surveys, and for experiments two to five (five experimental groups), 500 surveys per experiment. Our goal was to have, on average, 100 participants per experimental condition. For experiment one, we over-recruited experiment participants, because it was not entirely clear whether only completed surveys were considered part of the commissioned quota, or whether incomplete surveys also counted towards it. When it became obvious during experiment one that only completed surveys counted towards the commissioned quota, we decided not to over-recruit for experiments two and three. The numbers of completed surveys slightly diverge from the commissioned numbers. For experiment one, 244 instead of 250 surveys were completed; for experiment two, exactly 500; for experiment three, 504; for experiment four, 502; and for experiment five, 504. The crowdsourcing platform that we worked with thus has some imprecision in terms of commissioned vs. completed surveys, but the differences are within a ±2.5% range.

2.3 Design of experiment one: The lottery

We have conducted five experiments in order to test the impact of probabilistic information on conspiratorial reasoning. For experiment one, 244 participants (65% women, mean age = 34.8, SD = 11.9) were randomly assigned to two groups: 121 participants were assigned to the first group, and 123 participants were assigned to the second group. The participants in the first group were exposed to the following text:

```
John decides to buy a lottery ticket.  In order to win the
jackpot, John needs to choose 6 numbers correctly.

The next day, the lottery numbers are drawn:  John has
0 correct numbers.  Next week, John decides to buy a new
lottery ticket.  When the new numbers are drawn, John ends up
with 0 correct numbers again.

The statistical probability of ending up with 0 correct
numbers two weeks in a row is around 19%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...John was simply unlucky?
...the lottery was manipulated?
```

The order of the two questions at the end was randomized. The participants in the second group were exposed to the following text:

```
John decides to buy a lottery ticket.  In order to win the
jackpot, John needs to choose 6 numbers correctly.  The
next day, the lottery numbers are drawn:  John has 6 correct
numbers -- he has won the jackpot.

Next week, John decides to buy a new lottery ticket.  When
the new numbers are drawn, John ends up with 6 correct
numbers -- he has won the jackpot again.

The statistical probability of ending up with 6 correct
numbers two weeks in a row is around 0.0000000000005%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...John was simply lucky?
...the lottery was manipulated?
```

As in the first group, the order of the two questions at the end was randomized. After answering the questions about how likey they though it was that John was (un-)lucky and how likely they though it was that the lottery was manipulated, participants in both groups were asked to provide information on their gender, their age, and their country of residence. For the sake of simplicity, the gender options were female and male only. The probabilities of 19% in experiment one and 0.0000000000005% in experiment two are derived from a simple lottery setup with 49 numbers in total.

2.4 Design of experiment two: Falling roof tile (low impact, lack of clear ulterior motive)

For experiment two, 500 participants (64% women, mean age = 34.2, SD = 12.1) were randomly assigned to five groups: 82 participants were assigned to the first group, 105 to the second group, 101 to the third group, 108 to the fourth group, and 104 to the fifth group. The participants in all groups were exposed to a nearly identical text. The only difference, marked here as `XX%`, was the probabilistic information that each group received about the event in question:

```
John is walking down the street.  It's a windy day.

As he is walking, a roof tile suddenly hits John on the head.

According to roofers (experts in roof tiles), the probability
that a roof tile comes loose on a windy day is XX%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...the tile hit John by accident?
...someone dropped the tile on John's head on purpose?
```

The order of the two questions was randomized. In the text for the first group, the probability of a roof tile coming loose was presented to be 1%. In the second group, that probability was 25%; in the third group, it was 50%; in the fourth group, it was 75%; in the fifth group, it was 99%. As in experiment one, participants in both groups were asked to provide information on their gender, their age, and their country of residence upon answering the two questions about the common and the conspiratorial explanation. For the sake of simplicity, the gender options were female and male only.

Experiment two is a low-impact scenario (John being hit on the head is not of general concern for society), and the story lacks a clear ulterior motive.

2.5 Design of experiment three: Falling roof tile (low impact, clear ulterior motive)

For experiment three, 504 participants (61% women, mean age = 33.4, SD = 12.2) were randomly assigned to five groups: 101 participants were assigned to the first group, 91 to the second group, 103 to the third group, 108 to the fourth group, and 101 to the fifth group. As in experiment two, participants in all groups were exposed to a nearly identical text. The only difference, marked here as `XX%`, was the probabilistic information that each group received about the event in question:

```
John has recently broken up with his girlfriend.  His
girlfriend was very angry when John broke up with her.

One windy day, John is walking down the street.  A man stops
John and asks him for directions.  While John is explaining
the directions to the man, a roof tile suddenly hits John on
the head.

According to roofers (experts in roof tiles), the probability
that a roof tile comes loose on a windy day is XX%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...the tile hit John by accident?
...the man who stopped John did so on purpose so that John's
ex-girlfriend could attack John with the roof tile?
```

The order of the two questions was randomized. The probabilistic information for the five groups is the same as in experiment two. As in experiments one and two, participants in both groups were asked to provide information on their gender, their age, and their country of residence upon answering the two questions about the common and the conspiratorial explanation. For the sake of simplicity, the gender options were female and male only.

Experiment three is a low-impact scenario (John being hit on the head is not of general concern for society), just as experiment two. However, experiment three contains a clear ulterior motive.

2.6 Design of experiment four: Deceased journalist (high impact, lack of clear ulterior motive)

For experiment four, 504 participants (63% women, mean age = 33.4, SD = 12.0) were randomly assigned to five different groups: 90 participants were assigned to the first group, 105 to the second group, 90 to the third group, 96 to the fourth group, and 123 to the fifth group. Much as in experiments two and three, the participants in all groups of experiment three were exposed to a nearly identical text. The only difference, marked as `XX%`, was the probabilistic information that each group received:

```
John is an accomplished journalist.  He is found dead in his
apartment:  He died of a heart attack, officials declared.

According to doctors, the probability that someone like John
dies of a heart attack is XX%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...John really suffered a heart attack?
...John did not really suffer a heart attack, but that he was
actually murdered?
```

The order of the two questions was randomized. In the text for the first group, the probability of "someone like John" to die of a heart attack was presented to be 1%. The second group, that probability was 25%; in the third group, it was 50%; in the fourth group, it was 75%; in the fifth group, it was 99%. As in experiments one, two, and three, participants in both groups were asked to provide information on their gender, their age, and their country of residence upon answering the two questions about the common and the conspiratorial explanation. For the sake of simplicity, the gender options were female and male only.

Experiment four is a scenario with a high-impact story, the death and potential murder of a journalist, but there is no clear ulterior motive provided in the story.

2.7 Design of experiment five: Deceased journalist (high impact, clear ulterior motive)

For experiment five, 502 participants (64% women, mean age = 34.0, SD = 12.1) were randomly assigned to five different groups: 103 participants were assigned to the first group, 99 to the second group, 91 to the third group, 124 to the fourth group, and 85 to the fifth group. Once again, the participants in all groups of experiment five were exposed to a nearly identical text. The only difference, marked as `XX%`, was the probabilistic information that each group received:

```
John is an accomplished journalist who is critical of the
government.  He has just published an article where he
exposed a big corruption scandal in the government.

A day after the article has been published, John is found
dead in his apartment:  He died of a heart attack, officials
declared.

According to doctors, the probability that someone like John
dies of a heart attack is XX%.

What do you think:  How likely is it, from 0 (not at all
likely) to 10 (very likely), that...
...John really suffered a heart attack?
...John did not really suffer a heart attack, but that he was
actually murdered by the government?
```

The order of the two questions was randomized. The probabilistic information for the five groups is the same as in experiment four. As in experiments one to four, participants in both groups were asked to provide information on their gender, their age, and their country of residence upon answering the two questions about the common and the conspiratorial explanation. For the sake of simplicity, the gender options were female and male only.

Experiment five is a scenario with a high-impact story, the death and potential murder of a journalist, in combination with a clear motive, the government silencing a prominent critic.

2.8 Data analysis and researcher degrees of freedom

In any empirical scientific context, so-called researcher degrees of freedom (Simmons, Nelson, & Simonsohn, 2011) are a challenge. Researcher degrees of freedom describe the fact that between the start of the data collection and the reporting of results, researchers can make and have to make many decisions that determine the final reported results. Unfortunately, many of those decisions are not made *a priori*, but rather during and after the collection of the data. The general problem with researcher degrees of freedom is that researchers have intrinsic and extrinsic incentives to engage in so-called data dredging (Smith & Ebrahim, 2002) and *p*-hacking (Head, Holman, Lanfear, Kahn, & Jennions, 2015), and even in HARKing (Kerr, 1998) (hypothesizing after the results are known). *p*-hacking and HARKing are (at the very least) borderline unethical, but the problem of research degrees of freedom is present event when researchers don't actively and knowingly engage in practices such as *p*-hacking (Gelman & Loken, 2013).

In our analysis, we have actively sought to minimize researcher degrees of freedom and, where degrees of freedom are present, to make rational decisions. Researcher degrees of freedom in our three experiments pertain to three dimensions: Experiment design, data preparation, and data analysis.

In terms of *experiment design*, we have made the conscious decision to limit the data collected in the three experiment to precisely the data that is reported: The answers to the two main questions, and, in addition, information on participants' gender, age, and country of residence. We did not collect any additional data – the studies reported here are not, for example, only one part of a larger data set that will be used for additional publications.

In terms of *data preparation*, we have included all completed surveys into our data analyses. We did not exclude any cases.

In terms of *data analysis*, we have made two decisions. First, we are only looking at what is sometimes referred to as "main effects": We did not estimate any form of interaction effects, and we did not partition data into gender, age, or any other kind of sub-groups. We are simply estimating the data in its most direct form, because that is what we are interested in given our hypothesis. Furthermore, rather than engage in frequentist "significance testing", we are estimating means with the help of Bayesian estimation. Epistemologically, Bayesian estimation is attractive because it is a quantification of uncertainty that does not rely on a test statistic. The models we estimate are all of the following form:

$$y \sim t(\mu, \sigma, \nu)$$

$$\mu \sim \mathcal{N}(5, 5)$$
$$\sigma \sim Cauchy(0, 2)$$
$$\nu \sim Gamma(2, 0.1)$$

The models are estimated using the probabilistic modeling environment Stan (Carpenter et al., 2017) from within the statistical environment R (R Core Team, 2017). The modeling approach we use is a generalized version of a "robust" estimation of means whereby the Student's t distribution is used as the sampling distribution (Kruschke, 2013; Lange, Little, & Taylor, 1989). The models were estimated by running 4000 warmup and 4000 sampling iterations with three chains. The estimates converged well, as indicated by potential scale reduction factors (Gelman & Rubin, 1992) of $\hat{R} = 1$.

The model contains three parameters that are specified with priors; these priors represent researcher degrees of freedom. We have specified the prior for the mean μ as a normal distribution with mean 5 and standard deviation 5. Given the scale of the data y (0 - 10), the prior for μ is a rather simple very broad prior. The second parameter in the model, σ, is modeled as a half-Cauchy distribution (a Cauchy distribution truncated at 0) with scale 2. The half-Cauchy prior is a vaguely informative prior recommended for variance parameters (Polson & Scott, 2012). Finally, the normality parameter ν that governs the heaviness of the tails in the t distribution is modeled as a Gamma distribution with shape 2 and scale 0.1, which represents a vaguely informative prior (Juárez & Steel, 2010). The Bayesian modeling approach, then, does introduce additional researcher degrees of freedom, but since we are using the same specifications for all models, this means that we are not, for example, arbitrarily changing priors in order to create results that fit our hypothesis. Furthermore, we are consistently using vague priors, meaning that the data has much greater say than the likelihood. A practical benefit of the Bayesian approach is that it eliminates incentives for p-hacking: There are no p-values, and, therefore, there are no "significant" or "not significant" results in the sense of rules of thumb such as $p < 0.05$ equals "statistically significant".

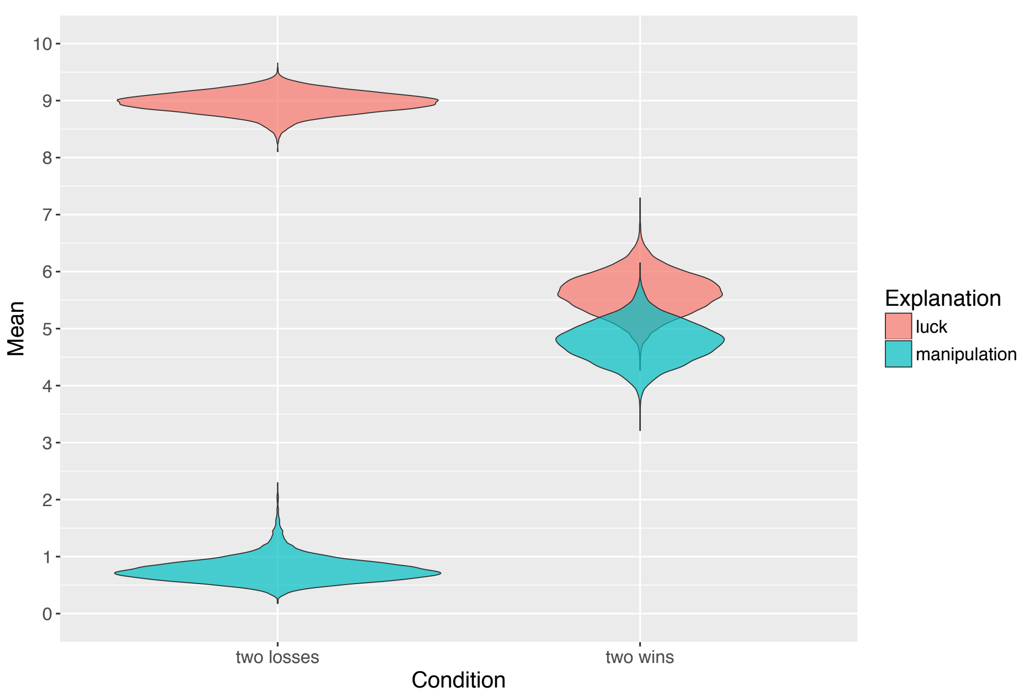
We have sought to minimize researcher degrees of freedom and to make rational decisions in those degrees of freedom that are present in our data analysis. In addition, all of our raw, unaltered data will be made available via the Open Science Framework.

3 Results

3.1 Experiment one: The lottery

The estimation results for experiment one are summarized in Figure 1.

Figure 1: *Estimated means for the responses in the two groups (conditions) of experiment one. The estimates for the common explanation are red, and the estimates for the conspiratorial explanation are blue.*



The violin plots in Figure 1 are visualizations of the posterior distribution of the estimated means for the two questions in each group. As can be plainly seen from Figure 1, the estimated means for the two groups are very different. The group that was exposed to the story about John losing twice very strongly believes in the common explanation (luck), and only very weakly in the conspiratorial explanation (manipulation). The situation is quite different in the group that read about John winning twice: The estimated means are very close to each other. The belief in the conspiratorial explanation (manipulation) is much stronger than is the case in the first group; so much so that there is no overlap between the posterior distribution for the conspiratorial explanation (manipulation) between the groups. This means that the true mean is almost certainly lower in the first, (relatively) high probability group (John losing twice) than in the second, low probability group (John winning twice). The same is true for the means of the common explanation (luck): The posterior distributions of the means of the two groups do not overlap, and, therefore, the real mean is almost certainly higher in the first group than in the second group.

The parameter estimates for experiment one are summarized in tabular form in Table 1.

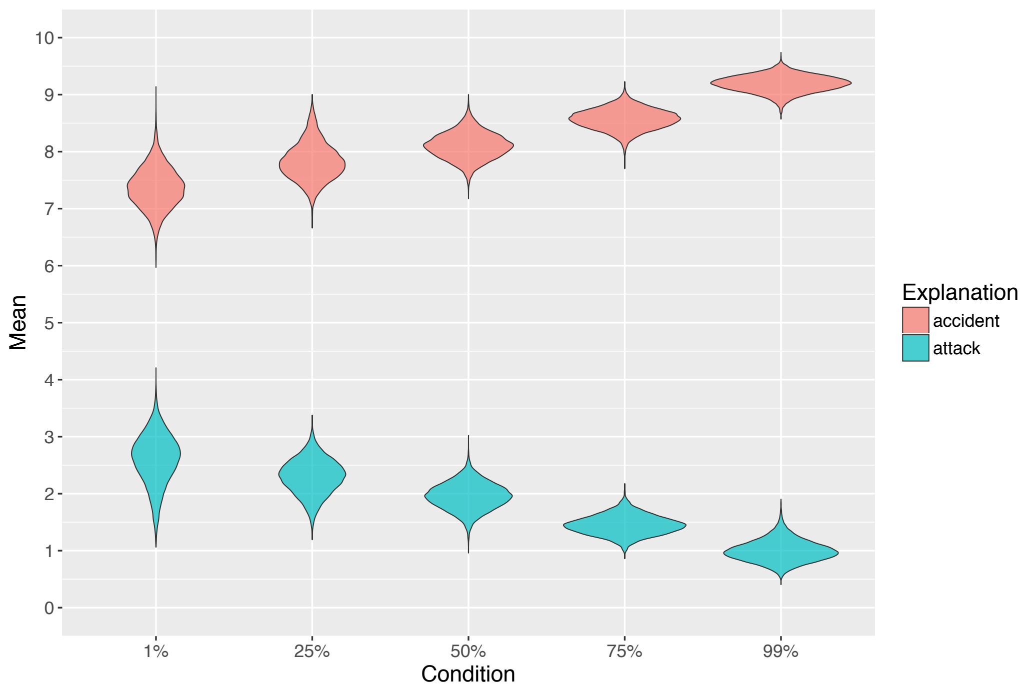
Table 1: *Summary of the parameter estimates of experiment one.*

Parameter	Condition	Explanation	mean	2.5%	97.5%	$\hat{R}$
μ	two losses	common	8.96	8.58	9.3	1
σ	two losses	common	1.27	0.96	1.66	1
ν	two losses	common	1.97	1.25	3.17	1
μ	two losses	conspiratorial	0.77	0.44	1.29	1
σ	two losses	conspiratorial	1.15	0.79	1.77	1
ν	two losses	conspiratorial	1.62	1.05	3.09	1
μ	two wins	common	5.62	4.94	6.31	1
σ	two wins	common	3.69	3.25	4.2	1
ν	two wins	common	34.95	12.81	73.81	1
μ	two wins	conspiratorial	4.77	4.1	5.43	1
σ	two wins	conspiratorial	3.64	3.21	4.15	1
ν	two wins	conspiratorial	35.22	12.9	73.86	1

3.2 Experiment two: Falling roof tile (low impact, lack of clear ulterior motive)

The results of the estimates for experiment two are summarized in Figure 2.

Figure 2: *Estimated means for the responses in the five groups (conditions) of experiment two. The estimates for the common explanation are red, and the estimates for the conspiratorial explanation are blue.*



The participants in all five groups clearly believe that the common explanation is much more probable than the conspiratorial one. However, the trend of the means for both explanations is one consistent with our hypothesis: The lower the alleged probability of the event, the higher, on average, the belief in the conspiratorial explanation (attack), and the lower the belief in the common explanation (accident). There is some overlap of the distributions of the 1% and of the 99% groups for both questions. This means that it is possible that the true trend of the means between the very low probability and the very high probability group is, in fact, flat or even opposite from what it appears to be visually. Since the distributions in Figure 2 are empirical in nature, we can quantify that probability. The probability that the means of the 1% and 99% groups for the common explanation (accident) lie within the band of overlapping areas is 0.18, and the probability that the trend of the two means, were they to lie in that band of overlapping areas, is either flat or negative is 0.09. Similarly, the probability that the means of the 1% and 99% groups for the conspiratorial explanation (attack) lie within the band of overlapping areas is 0.20, and the probability that the trend of the two means, were they to lie in within the band of overlapping areas, is either flat or negative is 0.03. Overall, then, the probability that the trends of the means between the very low probability and the very high probability group actually behave as hypothesized is high.

The parameter estimates for the common explanation in experiment two are summarized in tabular form in Table 2.

Table 2: *Summary of the parameter estimates for the common explanation in experiment two.*

Parameter	Condition	Explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	common	7.37	6.67	8.08	1
σ	1%	common	2.78	2.24	3.33	1
ν	1%	common	22.52	4.43	58.35	1
μ	25%	common	7.83	7.25	8.55	1
σ	25%	common	2.3	1.51	2.79	1
ν	25%	common	18.47	2.2	53.79	1
μ	50%	common	8.1	7.66	8.56	1
σ	50%	common	1.94	1.57	2.31	1
ν	50%	common	17.63	4.02	49.07	1
μ	75%	common	8.57	8.21	8.91	1
σ	75%	common	1.37	1.05	1.76	1
ν	75%	common	3.98	1.91	8.95	1
μ	99%	common	9.19	8.88	9.46	1
σ	99%	common	1	0.74	1.34	1
ν	99%	common	1.99	1.22	3.34	1

The parameter estimates for the conspiratorial explanation in experiment two are summarized in tabular form in Table 3.

Table 3: *Summary of the parameter estimates for the conspiratorial explanation in experiment two.*

Parameter	Condition	Explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	conspiratorial	2.6	1.6	3.38	1
σ	1%	conspiratorial	2.64	1.59	3.32	1
ν	1%	conspiratorial	17.68	1.87	53.15	1
μ	25%	conspiratorial	2.29	1.67	2.87	1
σ	25%	conspiratorial	2.17	1.5	2.67	1
ν	25%	conspiratorial	15.09	2.34	48.88	1
μ	50%	conspiratorial	1.96	1.49	2.41	1
σ	50%	conspiratorial	2.01	1.62	2.39	1
ν	50%	conspiratorial	18.65	4.23	50.42	1
μ	75%	conspiratorial	1.45	1.13	1.79	1
σ	75%	conspiratorial	1.25	0.93	1.6	1
ν	75%	conspiratorial	3.15	1.62	6.05	1
μ	99%	conspiratorial	1	0.66	1.41	1
σ	99%	conspiratorial	1.19	0.83	1.64	1
ν	99%	conspiratorial	2.19	1.23	4.23	1

3.3 Experiment three: Falling roof tile (low impact, clear ulterior motive)

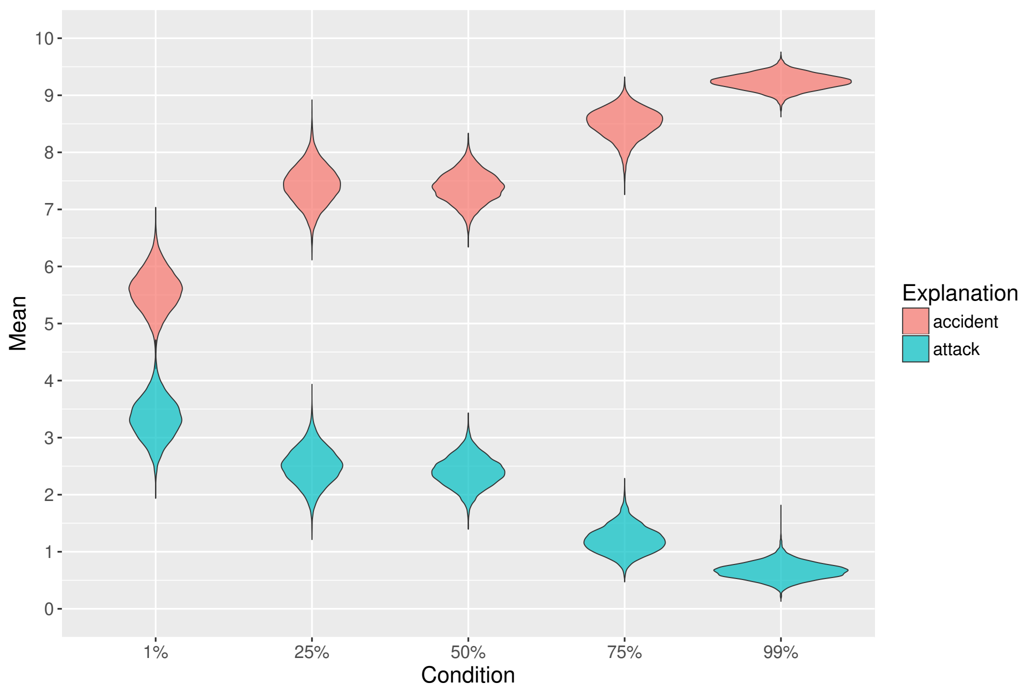
The results of the estimates for experiment three are summarized in Figure 3.

In comparison with the estimates for experiment two, the participants in experiment three have stronger beliefs in the conspiratorial explanation when presented with lower alleged probabilities. The difference in results between experiments two and three suggests that the presence of a clear ulterior motive has, ex expected, a mediating effect on conspiratorial belief. The overall trend of the estimated between conditions is not as smooth as in experiment two. However, neither the estimated distribution for the common nor for the conspiratorial explanation have any overlap between the 1% and the 99% groups, which suggests that the real trend of the means is as predicted between the very low probability and the very high probability groups.

The parameter estimates for the common explanation in experiment three are summarized in tabular form in Table 4.

The parameter estimates for the conspiratorial explanation in experiment three are summarized in tabular form in Table 5.

Figure 3: *Estimated means for the responses in the five groups (conditions) of experiment three. The estimates for the common explanation are red, and the estimates for the conspiratorial explanation are blue.*



3.4 Experiment four: Deceased journalist (high impact, lack of clear ulterior motive)

The results of the estimates for experiment four are summarized in Figure 4.

The trends for the estimated means of the belief in the common explanation (heart attack) and for the conspiratorial explanation (murder) in experiment four follow the pattern as predicted by our main hypothesis: The lower the alleged probability of the event, the stronger the belief in a conspiratorial explanation and the weaker the belief in the common explanation. As there is no overlap between the distributions of the 1% and the 99% groups, neither for the conspiratorial nor for the common explanation, the true trend between these two means cannot be flat or negative. In comparison to experiments two and three, the belief in the conspiratorial explanation is notably stronger (in the low probability groups). This lends support to the auxiliary hypothesis that a high-impact event increases the endorsment of

Table 4: Summary of the parameter estimates for the common explanation in experiment three.

Parameter	Condition	Explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	common	5.59	4.88	6.31	1
σ	1%	common	3.53	3.06	4.06	1
ν	1%	common	33.28	11.7	72.28	1
μ	25%	common	7.43	6.77	8.09	1
σ	25%	common	2.9	2.45	3.41	1
ν	25%	common	26.53	6.81	63.49	1
μ	50%	common	7.39	6.86	7.91	1
σ	50%	common	2.4	2	2.83	1
ν	50%	common	21.55	5.32	54.66	1
μ	75%	common	8.51	7.93	8.95	1
σ	75%	common	1.62	1.16	2.32	1
ν	75%	common	3.44	1.5	10.47	1
μ	99%	common	9.24	8.96	9.5	1
σ	99%	common	0.96	0.72	1.24	1
ν	99%	common	1.53	1.08	2.25	1

conspiratorial explanations.

The parameter estimates for the common explanation in experiment four are summarized in tabular form in Table 6.

The parameter estimates for the conspiratorial explanation in experiment four are summarized in tabular form in Table 7.

Table 5: Summary of the parameter estimates for the conspiratorial explanation in experiment three.

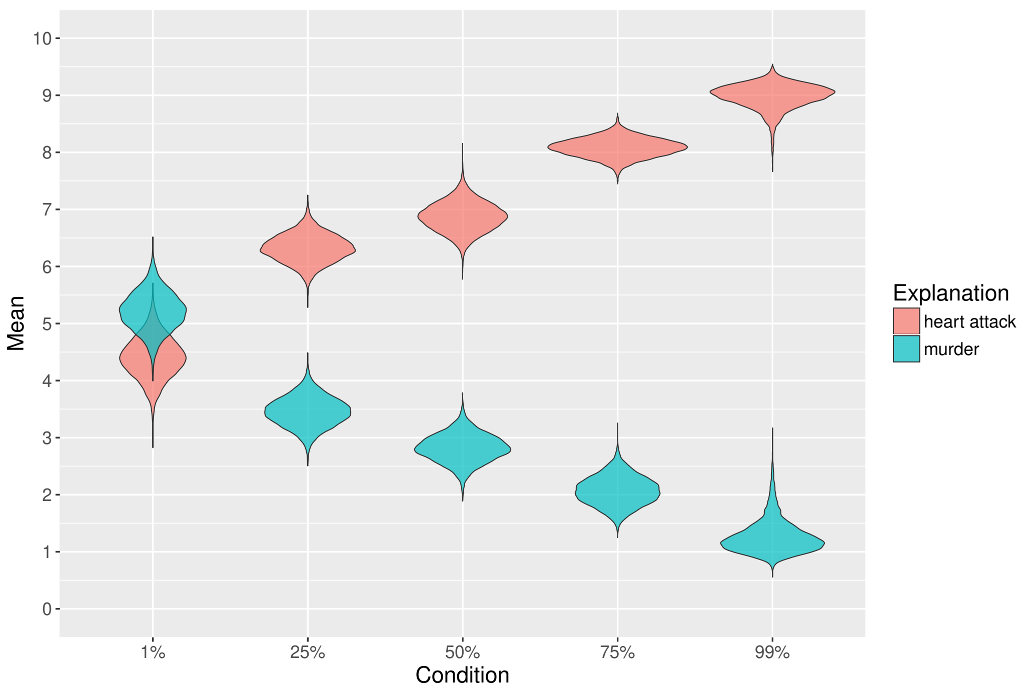
Parameter	Condition	Explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	conspiratorial	3.33	2.63	4.04	1
σ	1%	conspiratorial	3.4	2.94	3.93	1
ν	1%	conspiratorial	31.18	9.89	69.97	1
μ	25%	conspiratorial	2.5	1.86	3.12	1
σ	25%	conspiratorial	2.78	2.36	3.26	1
ν	25%	conspiratorial	27.19	7.58	64.17	1
μ	50%	conspiratorial	2.4	1.89	2.92	1
σ	50%	conspiratorial	2.45	2.06	2.85	1
ν	50%	conspiratorial	24.48	6.17	59.99	1
μ	75%	conspiratorial	1.21	0.8	1.72	1
σ	75%	conspiratorial	1.48	1.06	2.01	1
ν	75%	conspiratorial	4.35	1.69	14.51	1
μ	99%	conspiratorial	0.67	0.4	0.97	1
σ	99%	conspiratorial	0.95	0.7	1.3	1
ν	99%	conspiratorial	1.38	1.02	2.04	1

3.5 Experiment five: Deceased journalist (high impact, clear ulterior motive)

The results of the estimates for experiment three are summarized in Figure 5.

The overall trend of the estimated means once again follows the predicted pattern: The lower the alleged probability of the event, the stronger the belief in the conspiratorial and the weaker the belief in the common explanation. The estimated means of the 1% and the 99% groups partly overlap. While there is no overlap for the common explanation, there is some overlap for the conspiratorial explanation. The probability that the means lie in this band of area overlap is 0.19, and the probability that the trend of the means, were they to actually lie in that band of area overlap, is flat or positive is 0.01. It is therefore highly probable that the real trend of the means is negative. In comparison with the estimation results for experiment four, the overall belief in the conspiratorial explanation is much stronger. This lends further support to the auxiliary hypothesis that a clear ulterior motive increases the endorsement of conspiratorial beliefs. Within experiments two to five, the levels of conspiratorial belief are strongest in experiment five. This suggests that, as expected, conspiratorial beliefs are strongest in a high-impact, clear

Figure 4: *Estimated means for the responses in the five groups (conditions) of experiment four. The estimates for the common explanation are red, and the estimates for the conspiratorial explanation are blue.*



ulterior motive scenario.

The parameter estimates for the common explanation in experiment five are summarized in tabular form in Table 8.

The parameter estimates for the conspiratorial explanation in experiment five are summarized in tabular form in Table 9.

Table 6: *Summary of the parameter estimates for the common explanation in experiment four.*

	condition	explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	common	4.4	3.69	5.13	1
σ	1%	common	3.25	2.8	3.79	1
ν	1%	common	30.87	9.92	68.22	1
μ	25%	common	6.32	5.84	6.8	1
σ	25%	common	2.38	2.05	2.75	1
ν	25%	common	28.02	8.51	65.07	1
μ	50%	common	6.87	6.37	7.38	1
σ	50%	common	2.28	1.94	2.69	1
ν	50%	common	24.29	6.62	59.59	1
μ	75%	common	8.08	7.76	8.4	1
σ	75%	common	1.47	1.21	1.75	1
ν	75%	common	18.65	4.55	51.09	1
μ	99%	common	8.98	8.45	9.32	1
σ	99%	common	1.24	0.85	1.89	1
ν	99%	common	1.92	1.09	4.19	1

Table 7: *Summary of the parameter estimates for the conspiratorial explanation in experiment four.*

	condition	explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	conspiratorial	5.21	4.53	5.9	1
σ	1%	conspiratorial	3.11	2.68	3.62	1
ν	1%	conspiratorial	30.34	9.84	68.09	1
μ	25%	conspiratorial	3.46	2.94	3.97	1
σ	25%	conspiratorial	2.57	2.23	2.96	1
ν	25%	conspiratorial	27.93	8.7	64.55	1
μ	50%	conspiratorial	2.82	2.32	3.3	1
σ	50%	conspiratorial	2.2	1.88	2.58	1
ν	50%	conspiratorial	26.63	7.7	62.38	1
μ	75%	conspiratorial	2.07	1.6	2.57	1
σ	75%	conspiratorial	1.78	1.28	2.26	1
ν	75%	conspiratorial	9.97	2.29	36.23	1
μ	99%	conspiratorial	1.27	0.87	2.09	1
σ	99%	conspiratorial	1.39	0.88	2.39	1
ν	99%	conspiratorial	2.27	1.06	7.67	1

Figure 5: *Estimated means for the responses in the five groups (conditions) of experiment five. The estimates for the common explanation are red, and the estimates for the conspiratorial explanation are blue.*

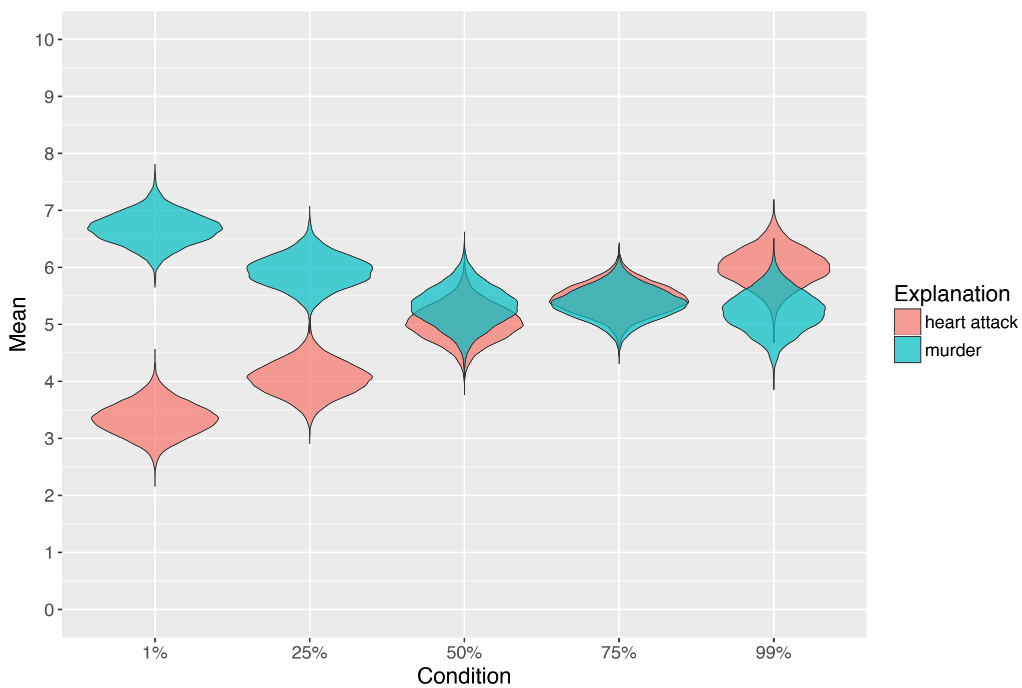


Table 8: *Summary of the parameter estimates for the common explanation in experiment five.*

	condition	explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	common	3.34	2.79	3.91	1
σ	1%	common	2.74	2.35	3.19	1
ν	1%	common	26.99	7.73	62.75	1
μ	25%	common	4.05	3.48	4.63	1
σ	25%	common	2.79	2.4	3.24	1
ν	25%	common	29.19	8.85	66.15	1
μ	50%	common	5.02	4.4	5.65	1
σ	50%	common	2.87	2.46	3.36	1
ν	50%	common	28.62	8.58	66	1
μ	75%	common	5.45	4.93	5.96	1
σ	75%	common	2.79	2.43	3.19	1
ν	75%	common	31.21	10.06	70.36	1
μ	99%	common	6	5.36	6.64	1
σ	99%	common	2.83	2.41	3.34	1
ν	99%	common	28.03	7.97	65.05	1

Table 9: *Summary of the parameter estimates for the conspiratorial explanation in experiment five.*

	condition	explanation	mean	2.5%	97.5%	$\hat{R}$
μ	1%	conspiratorial	6.68	6.15	7.23	1
σ	1%	conspiratorial	2.61	2.23	3.04	1
ν	1%	conspiratorial	26.26	7.32	62.6	1
μ	25%	conspiratorial	5.93	5.38	6.48	1
σ	25%	conspiratorial	2.69	2.31	3.13	1
ν	25%	conspiratorial	28.82	8.87	64.64	1
μ	50%	conspiratorial	5.32	4.65	5.98	1
σ	50%	conspiratorial	3.06	2.63	3.58	1
ν	50%	conspiratorial	30.14	9.6	67.13	1
μ	75%	conspiratorial	5.36	4.82	5.89	1
σ	75%	conspiratorial	2.87	2.52	3.27	1
ν	75%	conspiratorial	32.41	11.22	69.32	1
μ	99%	conspiratorial	4.54	5.89	5.89	1
σ	99%	conspiratorial	2.62	3.6	3.6	1
ν	99%	conspiratorial	9.74	67.4	67.4	1

4 Discussion

4.1 Limitations of this study

Besides the general limitations of any singular study (the main hypothesis needs to be further explored and the experiments replicated), we suspect that the framing of our experiments biased participants' responses. More specifically, we have presented the alleged probabilities for events as $\Pr(event \mid chance)$. The participants were asked to estimate $\Pr(chance \mid event)$ and $\Pr(conspiracy \mid event)$. It is possible that some or even all participants have simply interpreted $\Pr(event \mid chance)$ as $\Pr(chance \mid event)$ and $\Pr(conspiracy \mid event)$ as $1 - \Pr(event \mid chance)$. Even though both of those deductions are incorrect, the framing of the experiments might have nudged the participants towards such an interpretation. Future research on the relationship between probability and conspiratorial thinking should therefore be designed in a way that avoids this potential bias.

4.2 Conspiratorial thinking as a possible cognitive heuristic

Overall, the five experiments lend support to the hypothesis we set out to test: The lower the probability of an event, the stronger the belief in a conspiratorial explanation, and the weaker the belief in the common explanation. In addition, the results suggest that high-impact scenarios as well as scenarios with clear ulterior motives induce stronger belief in conspiratorial explanations. These results are not all that surprising in light of what is known about how humans handle probabilities: A number of cognitive biases are, in essence, errors in probabilistic thinking, and conspiratorial reasoning might represent just another such bias. For example, we know that humans tend to have a difficult time with handling low probability events, especially if the events in question have both low probability and high impact; this trait is sometimes described with the black swan metaphor (Taleb, 2010; Wardman & Mythen, 2016). In this context, conspiratorial thinking as a potential cognitive bias might represent a general strategy for handling probabilistic information, or, expressed more generally, a coping strategy for uncertainty, since probability is a quantification of uncertainty.

If conspiratorial thinking occurs as a general cognitive bias and not only as a pathology of the mind, that means that it might also be possible to devise countermeasures against conspiratorial thinking that have an effect of generalized debiasing (Croskerry, Singhal, & Mamede, 2013; Lilienfeld, Ammirati, & Landfield, 2009). In order to tackle specific singular conspiracy theories, "debunking" them might work. In order to tackle conspiratorial thinking in general, metacognitive debiasing as a form of training in probabilistic thinking might be more effective.

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